Smart Algorithm Based on the Optimization of SVR Technique by k-NNR Method for the Prognosis of the Open-Circuit and the Reversed Polarity Faults in a PV Generator

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Abstract – *This paper deals with a new smart algorithm allowing open-circuit and reversed polarity faults prognosis in photovoltaic generators. Its contribution lies on the optimization of support vector regression (SVR) technique by a k-NN regression tool (k-NNR) for undetermined outputs.*

To testing the performance of the proposed algorithm, we used a significant data base containing the generator functioning history, and as indicators we selected variance, standard deviation, Confidence interval, absolute and relative errors.

***Keywords**: Photovoltaic Generator, SVR, k-NNR, Open-Circuit, Reversed Polarity, Diagnosis, Prognosis, Lab-VIEW.*

Nomenclature

PV	Photovoltaic
SVM	Support Vector Machines
SVR	Support Vector Regression
k-NNR	k-Nearest Neighbor Regression
X	SVR input vector
Y	SVR output vector
f	Linear function
Φ	Nonlinear mapping function
w	Weight vector
e	Squared loss function
x	Problem variable
x^*	New problem variable
α	Lagrange multipliers
N	Number of classes
m	Number of index of minimum distances
I / V	Current / Voltage
IPH	Photocurrent

I. Introduction

The performance index is a value independent of place and measuring the PV system production [1]-[3]. Really, this performance index is often called the quality factor. It indicated as a percentage, means the ratio between the actual and the theoretical PV system energy. So, it shows the share of the available actually energy, after deducting the specific operating consumption by the installation, and the energy losses (thermal and conduction losses).

So, these energy losses can be caused by the presence of defects, like the open-circuit and reversed polarity. However, provided a better prognosis [9]-[12] and diagnosis [14]-[16] functions of the generator can stabilize its performance and ensure its availability and reliability.

In this context, the paper objective is the development of an algorithm for the prognosis of a photovoltaic generator state, under open-circuit and reversed polarity faults. Indeed, the paper contributions are twofold: *1)* development an algorithm for the detection and the localization of the open-circuit and reversed polarity faults at the PV generator components: cells, bypass and blocking diodes, it bases on the analysis of the operating parameters of the generator. *2)* Development of a smart prognosis algorithm for the characterization of the open-circuit and reversed polarity faults, regardless of their localization. It bases on the support vector regression (SVR) [19]-[22] optimized by the k-nearest neighbor method [23]-[26].

II. Classical Diagnosis Algorithm

This new proposed algorithm is for objective to detecting and locating the open-circuit and reversed polarity faults on the generator components: PV cells, bypass and blocking diodes.

The following figure shows the studied generator (Fig.1), which contains five strings in parallel, where each string comprises five modules in series, and ended by blocking diode. Each module contains two groups in series. Finally, each group composes of eighteen cells in series regrouped by one bypass diode in parallel.

This new proposed algorithm consist mainly four steps:

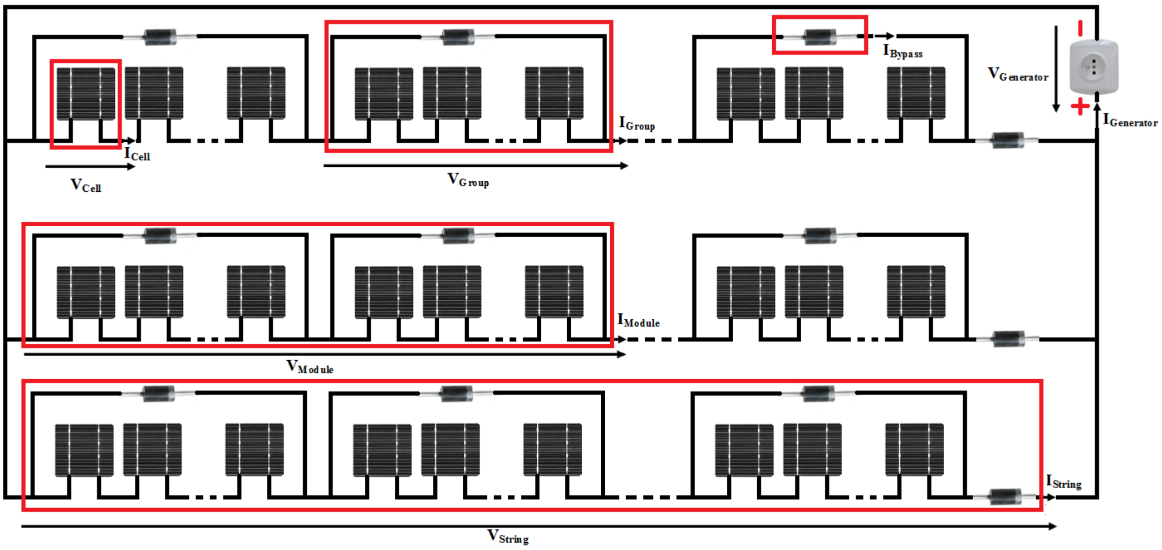

Fig.1 . Photovoltaic generator described

A) Step1: if the generator characteristic is

$$\begin{cases} V_{PV} = V_{PV\_Open-Circuit} \\ I_{PV} = 0 \end{cases} \quad (1)$$

indicates that the generator is open-circuit. But, if its characteristic is

$$\begin{cases} 0 \le V_{PV} \le V_{PV\_Opposite} \\ -I_{PV\_Opposite} \le I_{PV} \le 0 \\ PHI = 0 \end{cases} \quad (2)$$

mains that the generator is subjected to a reversed polarity fault. Also, if its characteristic is

$$\begin{cases} -V_{PV\_Healthy} \le V_{PV} \le V_{PV\_Healthy} \\ 0 < I_{PV} < I_{PV\_Healthy} \\ PHI \ne 0 \end{cases} \quad (3)$$

designates that the generator contains at least one string with components in reversed polarity fault.

B) Step2: if the string characteristic is

$$\begin{cases} V_{String} = V_{String\_Open-Circuit} \\ I_{String} = 0 \end{cases} \quad (4)$$

indicates the presence of at least one of these defects: connections between modules open-circuit, blocking diode open-circuit or modules open-circuit. But, if its characteristic is

$$\begin{cases} I_{String\_Cells} = 0 \\ I_{String} = I_{String\_Opposite} < 0 \\ PHI = 0 \\ V_{String} = V_{String\_Opposite} \end{cases} \quad (5)$$

mains that its blocking diode under reversed polarity. Also, if its characteristic is

$$\begin{cases} 0 < I_{String} < I_{String\_Healthy} \\ -V_{String\_Healthy} \le V_{String} \le V_{String\_Healthy} \\ I_{String\_Opposite} = 0 \\ IPH \ne 0 \end{cases} \quad (6)$$

designates that this string contains at least one module under reversed polarity.

C) Step3: if the module characteristic is

$$\begin{cases} I_{Module} = 0 \\ V_{Module} = V_{Module\_open-circuit} \end{cases} \quad (7)$$

mains the presence of at least one of group open-circuit, or connection between groups open-circuit. But, if its characteristic is

$$\begin{cases} 0 < I_{Module} < I_{Module\_Healthy} \\ -V_{Module\_Healthy} < V_{Module} < V_{Module\_Healthy} \end{cases} \quad (8)$$

designates the presence of module in reversed polarity.

D) Step4: the PV group is open-circuit if

$$\begin{cases} I_{Group} = 0 \\ V_{Group} = V_{Group\_open\ circuit} \end{cases} \quad (9)$$

Also, if its characteristic is

$$\begin{cases} I_{Group} \ne 0 \\ V_{Group} = V_{Group\_Open-Circuit} \end{cases} \quad (10)$$

designates the existence of cells open-circuit, Or connections between cells open-circuit. In addition, if its characteristic is

$$\begin{cases} I_{Group} = 0 \\ V_{Group} = 0 \\ IPH = 0 \end{cases} \quad (11)$$

indicates that this group contains a bypass diode open-circuit. But, if the group characteristic is

$$\begin{cases} I_{Group} = I_{Group\_Healthy} \\ 0 < V_{Group} < V_{Group\_Healthy} \end{cases} \quad (12)$$

mains the presence of group contains at least cell under reversed polarity, with the number of healthy cells is greater than the defective ones. Also, if its characteristic is

$$\begin{cases} I_{Group} = I_{Cells} + I_{Bypass\ diode} \\ -V_{Cells\_Healthy} \leq V_{Group} \leq 0 \end{cases} \quad (13)$$

designates the existence of group contains at least half of its cells under reversed polarity. And finally, if its characteristic is

$$\begin{cases} I_{Group} = I_{Cells\_Healthy} - I_{Bypass\ diode} \\ V_{Group} = 0 \end{cases} \quad (14)$$

Indicates that this group is grouped by a bypass diode in reversed polarity.

III. Intelligent Prognosis Algorithm

III.1. SVR Algorithm

Regression by support vector machines (Support Vector Regression) is an extension of support vector machines developed by the VAPNIK group. The purpose of this approach is to determine the optimal hyper-plane representing the dataset. This hyper-plane must interpolate the observations with some margin, which defined by the insensitivity loss function. The main advantages of this approach are its robustness against noise and errors, also the possibility of its use in the nonlinear case through the kernel functions.

Consider a set of data: $\{(x_1,y_1),\ldots,(x_n,y_n)\} \subset X$, where X represents the data space. In support vector regression, the objective is to find the function $f(x)$, which has at most a deviation of ε, compared to the y_i targets of all dataset, and at the same time which is flat as possible.

SVR general pattern of regression in its linear and nonlinear cases is as follows

$$\begin{cases} \text{If the problem is linearly separable} \\ \quad f(x) = \langle w, x \rangle + b \\ \text{Else} \\ \quad f(x) = \langle w, \phi(x) \rangle + b \end{cases} \quad (15)$$

The aim therefore at this point is to determine the function parameters, which is the weight *w*, and the bias *b*, which minimize the SVR margin, this leads to a least squares to simplify the SVR problem to a system of linear equalities. The regression problem becomes then as follows.

$$\begin{cases} \text{If the problem is linearly separable} \\ \quad f(x) = \left[\langle x, x_1 \rangle \langle x, x_2 \rangle \ldots \langle x, x_N \rangle \right] \alpha + b \\ \text{Else} \\ \quad f(x) = \left[\langle \phi(x), \phi(x_1) \rangle \ldots \langle \phi(x), \phi(x_N) \rangle \right] \alpha + b \end{cases} \quad (16)$$

As all regression techniques, this tool has some disadvantages that can degrade its effectiveness, among them the existence of indeterminate outputs for some observations. The outputs of the regression model are generally of good quality when they are determinate.

Consequently, we are proposed and after a research bibliography interesting as solution the k-nearest neighbors, thanks to its advantages in the regression area. The use of this tool is for the outputs approximations of these some observations have indeterminate outputs by SVR.

III.2. k-NN Regression Algorithm

k-NN is a method based on memory, which unlike other statistical methods does not require any learning (that is to say there is no model to adjust). It belongs to the Prototypes methods category. It operates on the intuitive principle, which the nearest objects are most likely to belong to the same category. Thus, with the *k-NN* method, the forecasts are based on a set of prototypes examples, which are used to predict new data, based on the average for the regression of the *k* nearest prototypes.

The choice of *k* is essential in the k-NN model construction, because it can strongly influence the forecasts quality. For a given problem, a low value of *k* will lead to a large variance in the forecast. Contrary, if you assign a high *k* value, you will introduce significant bias in the model, because it can minimize the regression error probability.

After selecting the *k* value, the forecasts assignment is based on the examples of k-NN. For regression problems, forecasts k-NNs are calculated as the average of the *k* nearest neighbors.

$$y = \frac{1}{k} \sum_{j=1}^{k} y_i \quad (17)$$

Where y_i is the i^{th} sample observation of examples, and *y* is the forecast (result) of the query point.

III.3. The Proposed Smart Algorithm

In this section, we proposed a new smart algorithm allowing smart prognosis of a PV generator. This new model is firstly used SVR technique bases on its kernel function on Gaussien type, for all observations have determined outputs. And secondly, it used k-NNR tool that aims to approximate the observations outputs that have undetermined outputs predict by SVR technique. The hybridization of these two methods leads to the following formulation.

$$\begin{cases} \text{If the problem is linearly separable} \\ f(x) = (1-\theta)\left(\begin{matrix}\left[\langle x,x_1\rangle\langle x,x_2\rangle\ldots\langle x,x_N\rangle\right]\alpha + \\ \left[y_i - e_i - \langle w,x_i\rangle\right]\end{matrix}\right) + \theta \dfrac{\sum_{p=1}^{m}\left(\begin{matrix}\left[\langle x_{[\text{index}_p]},x_1\rangle\langle x_{[\text{index}_p]},x_2\rangle\ldots\langle x_{[\text{index}_p]},x_N\rangle\right]\alpha+\\ \left[y_i-e_i-\langle w,x_i\rangle\right]\end{matrix}\right)}{m} \\ \text{Else} \\ f(x) = \left[\begin{matrix} (1-\theta)\left(\left[\langle\phi(x)\phi(x_1)\rangle\langle\phi(x)\phi(x_2)\rangle\ldots\langle\phi(x)\phi(x_N)\rangle\right]\alpha+\left[y_i-e_i-\langle w,\phi(x_i)\rangle\right]\right) \\ +\theta\left(\dfrac{\sum_{p=1}^{m}\left(\left[\langle\phi(x_{[\text{index}_p]})\phi(x_1)\rangle\langle\phi(x_{[\text{index}_p]})\phi(x_2)\rangle\ldots\langle\phi(x_{[\text{index}_p]})\phi(x_N)\rangle\right]\alpha+\left[y_i-e_i-\langle w,\phi(x_i)\rangle\right]\right)}{m}\right)\end{matrix}\right]\end{cases} \quad (18)$$

$\theta = 0$ for determined SVR results, else $\theta = 1$. i=1:1:N.

IV. Simulations Results

IV.1. Faulted PV Generator Characterization

The results simulations of classical diagnosis algorithm by Lab-VIEW software are shown in the following Figs. 2 to 7.

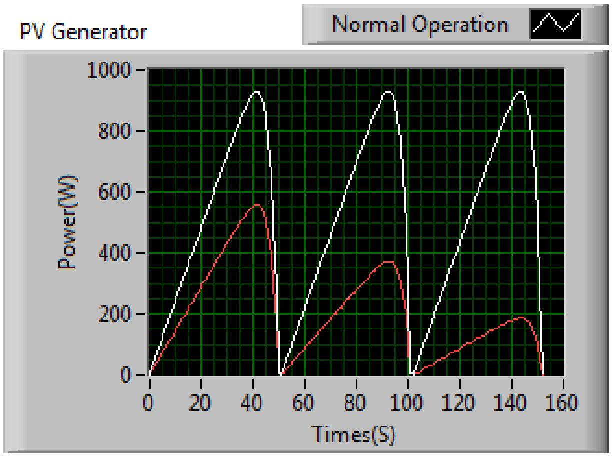

Fig2. Open circuit cells influence on the PV generator operation.

1) Fig. 2 presents the future operation of the defective PV generator subjected successively to 1, 2, 3 defective groups, where everyone contains a cell open-circuit. It shows that the open-circuit influence is not remarkable on the generator current, except where one of its strings all its groups are defective. But, it can increase the generator voltage, if all its strings are defective, and it increased in proportion to the increase in the number of its faulty groups, until it reaches its open-circuit value, and its current becomes zero.

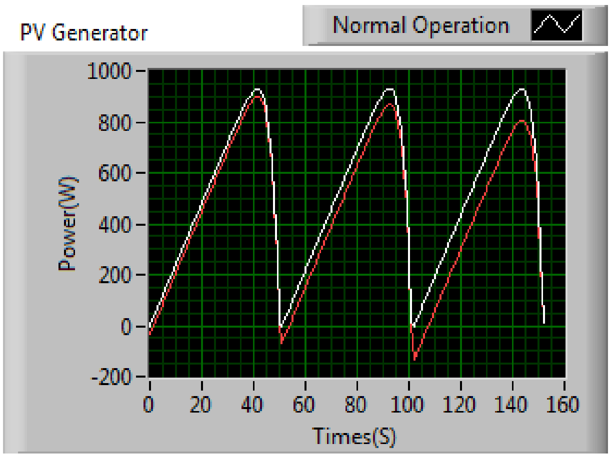

Fig3. Cells reversed polarity influence on the PV generator operation.

2) Fig. 3 presents the future operation of the PV generator in the presence of successively 5, 10, 15 cells reversed polarity. It shows that the generator power decreases proportionally to the number of defective cells, until will be null in the case where half of its cells are defective. Also, the PV generator absorbs power if the number of its defective cells greater that the healthy ones.

3) Fig. 4 shows an operating mode of the faulty PV generator with a power output as the normal operation, but it subjected to the presence of successively 10, 20, 50 bypass diodes reversed polarity. Therefore, the absence of the photocurrent on the last group of each string in the third phase of the PV generator operation discovers the

presence of bypass diodes open-circuit. Consequently, the bypass diode open-circuit defect is classified among the major flaws, because its detection is difficult and requires to other parameters such as the sunlight. So, we concluded that the influence of this defect is not remarkable on the characterization of the generator, as long as the cells group assembled by these defective diodes is in the normal functioning.

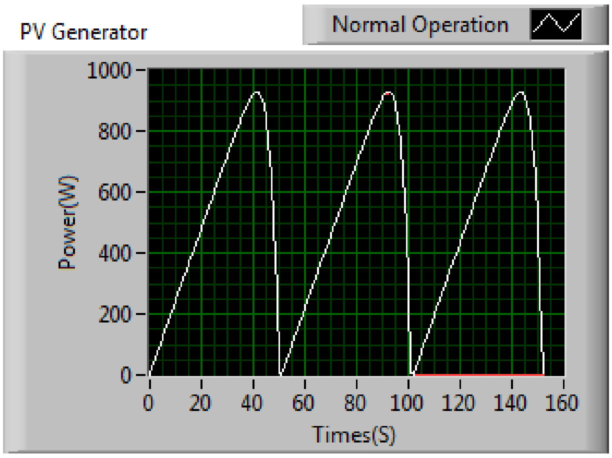

Fig4. Open circuit bypass diodes influence on the PV generator operation.

4) Fig. 5 shows the presence influence of successively 2, 3, 8 faulty groups, where each one contains one bypass diode reversed polarity on the future operation of the PV generator. It shows that the bypass diode reversed polarity has a greater impact on the PV generator performance, because it can cancel outright its group voltage.

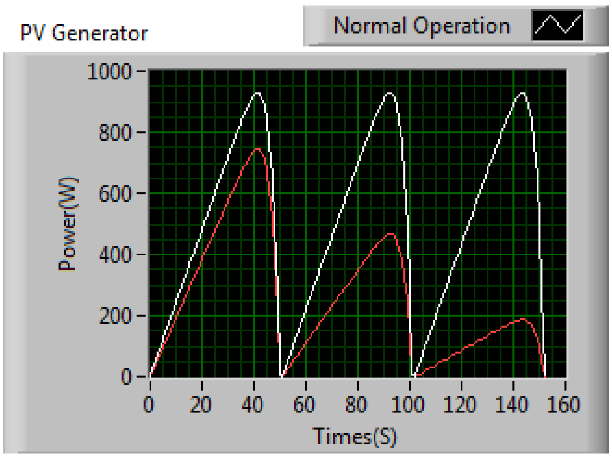

Fig5. Bypass diodes reversed polarity influence on the PV generator operation

Fig. 6 shows the future operation of PV generator contains successively the presence of 2, 3, 4 defective blocking diodes open-circuit. It shows that the open-circuit defect can cut the current flowing across the faulty string, and therefore increases its voltage to its open-circuit value. Its influence is not remarkable on the generator voltage contains at least one good string, but its current is reduced in proportion to the increase in the number of blocking diode open-circuit, up to becomes zero, thereby its voltage takes its open-circuit value.

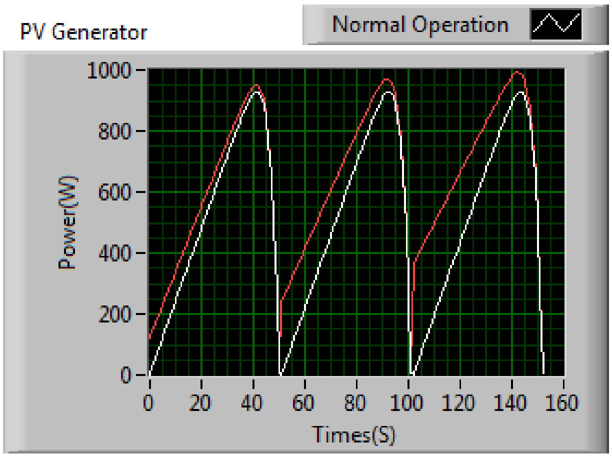

Fig6. Blocking diode open circuit influence on the PV generator operation.

Fig. 7 presents the case of the presence of successively 1, 2, 3 blocking diodes reversed polarity in the future operation of the PV generator. It shows that the reversed polarity defect can degrade the generator power, because the existence of one defective blocking diode can affect the string current flow, and this string behaves in the open-circuit mode.

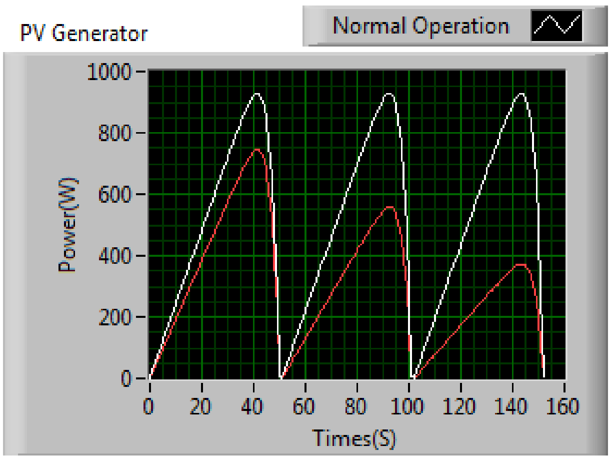

Fig7. Blocking diode reversed polarity influence on the PV generator operation.

IV.2. Smart Algorithm Tests

In this context, three 50 identical samples are selected (total sum = 150 samples), each sample containing 950 observations, each observation constituted six parameters which are: current *I*, voltage *V*, power *P*, series resistance R_s, temperature *T* and photocurrent I_{ph}, but this observation is presented in this simulation by its center of gravity '*x*', so the 47500 observations (50 samples * 950 observations) are distributed on four classes types which are: normal functioning, cells open-circuit and reversed polarity, bypass diodes open-circuit and reversed polarity and finally blocking diodes open-circuit and reversed polarity [27]-[28]. In this application, we are used for each 50 samples one of the three regression tools used for comparison purposes: SVR, k-NNR, and the proposed model SVR optimized by k-NNR.

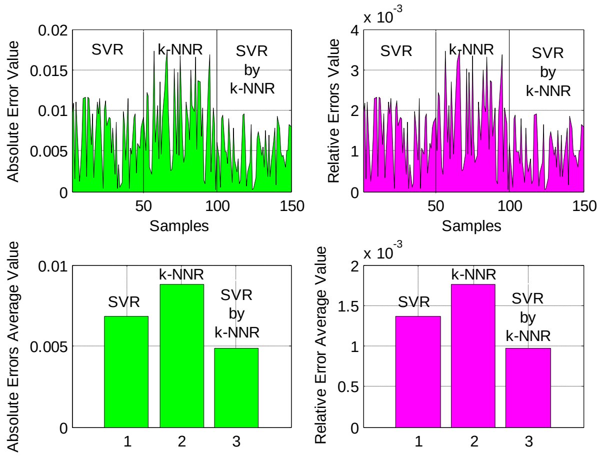

Fig. 8. Absolute and relative errors *vs* prediction tools.

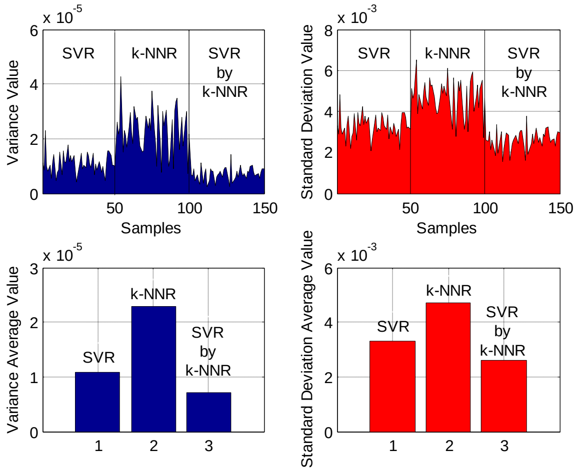

Fig. 9. Variance and standard deviation *vs* prediction tools.

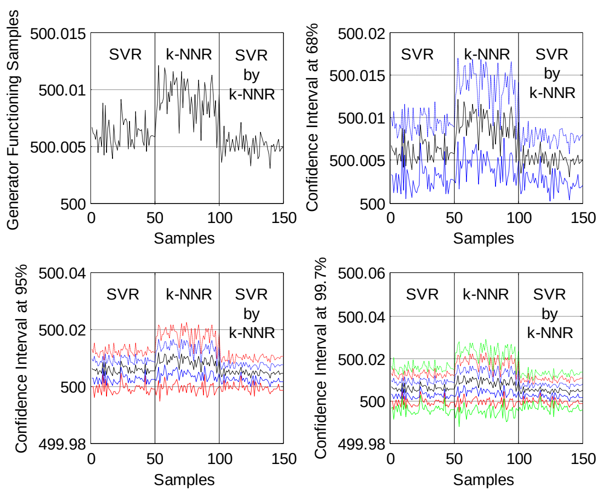

Fig. 10. Confidence interval *vs* prediction tools.

Fig. 8 illustrates the prediction performance in terms of absolute and relative errors. It shows that the k-NNR has a greater absolute and relative error. Then, in a descending orders successively the SVR tool, and finally the proposed model that provides the smallest absolute and relative error in these all tools. This means that the proposed model achieves the best prediction performance.

Fig. 9 illustrates the second criterion used for the prediction performance evaluation: variance and standard deviation. It shows that the k-NNR has the greater standard deviation and variance. Then, in a descending orders successively SVR, and finally the proposed model, which has a smallest standard deviation and variance. This means that the predicted results of the proposed method are more homogeneous.

The third evaluation criterion used is the confidence interval. In this case, Fig. 10 shows that the k-NNR provides a larger confidence interval, then SVR tool, then finally the proposed model that has the confidence interval the most optimized. This means that the predicted results of the proposed method are more reliable.

V. Conclusion

In this article, we are proposed a new smart prognosis algorithm for the open-circuit and reversed polarity faults, in a photovoltaic generator. The proposed prognosis (prediction) approach is based on the use of SVR tool, optimized by k-NNR for undetermined outputs.

The study and analysis of the results obtained from the simulation based on the determination of the absolute and relative error, standard deviation and variance, and finally the confidence margin, shows that the new contribution achieves the best prediction performance with more homogeneous and reliable prediction results.

The future work of this algorithm lies in the prognosis of the hybridization of the two defects open-circuit and reversed polarity, which can present at the same component and in the same time.

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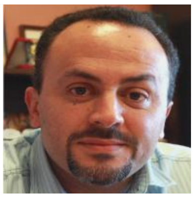

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